



E298A/EE290B – Electron Beam Lithography systems II: Alignment/Calibration

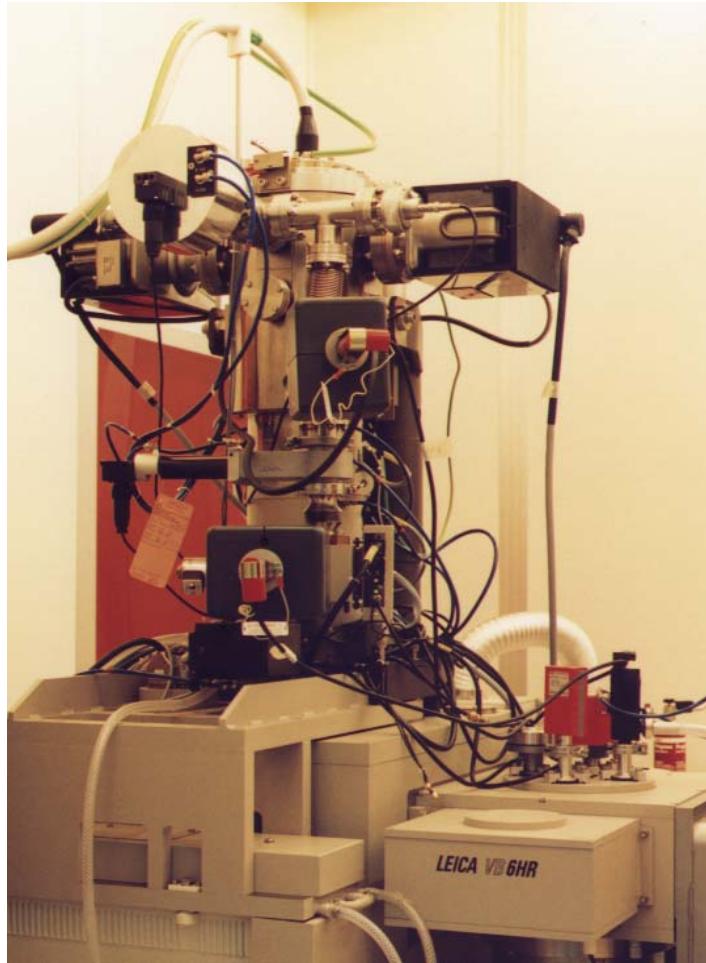


- Purpose: Understand the alignment and calibration procedures for the Nanowriter system
 - Automatic focus/stigmation with Image Processing
 - Determination of calibration coefficients with more equations than unknowns
 - Singular Value Decomposition
 - Position determination with Image Processing





Calibration and Alignment



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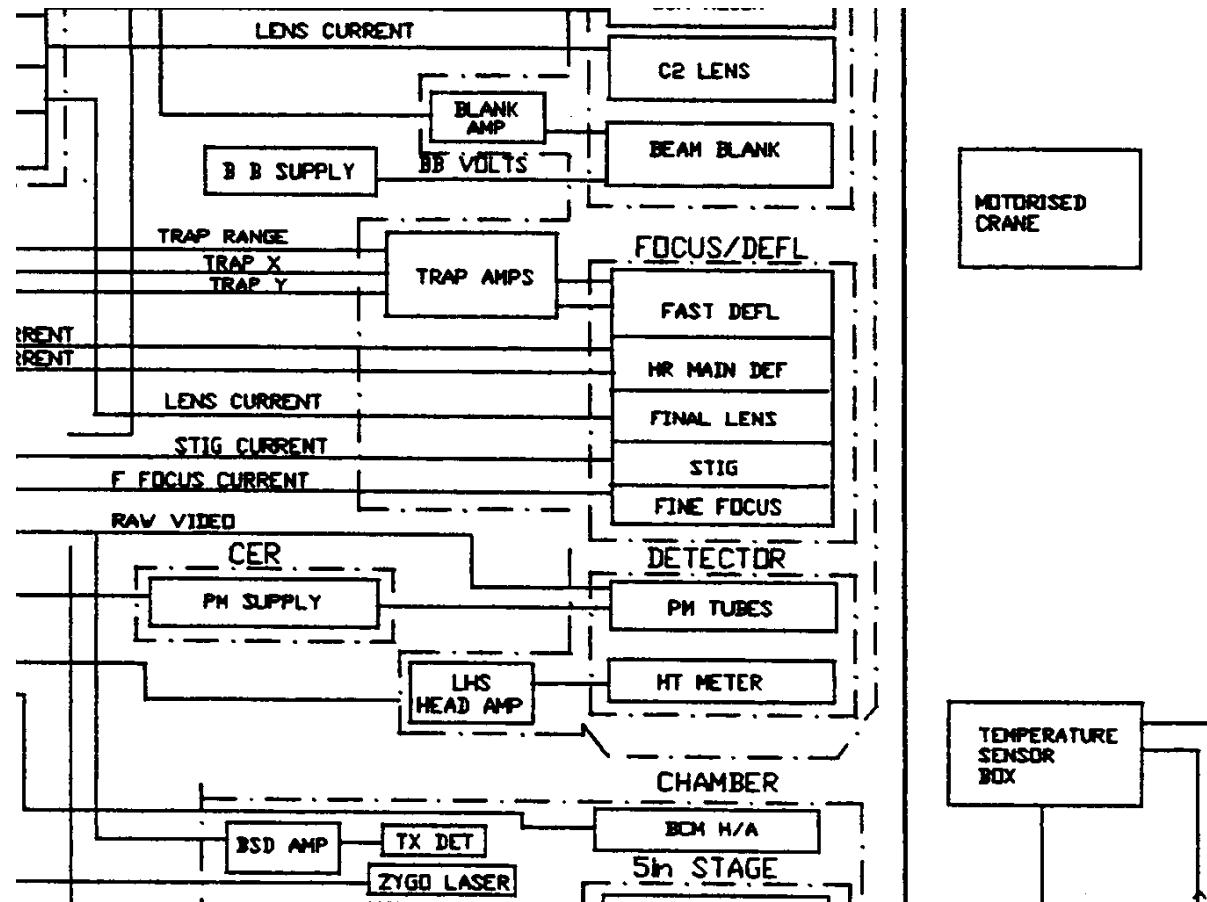
Lecture 9 Alignment/Calibration



System Architecture



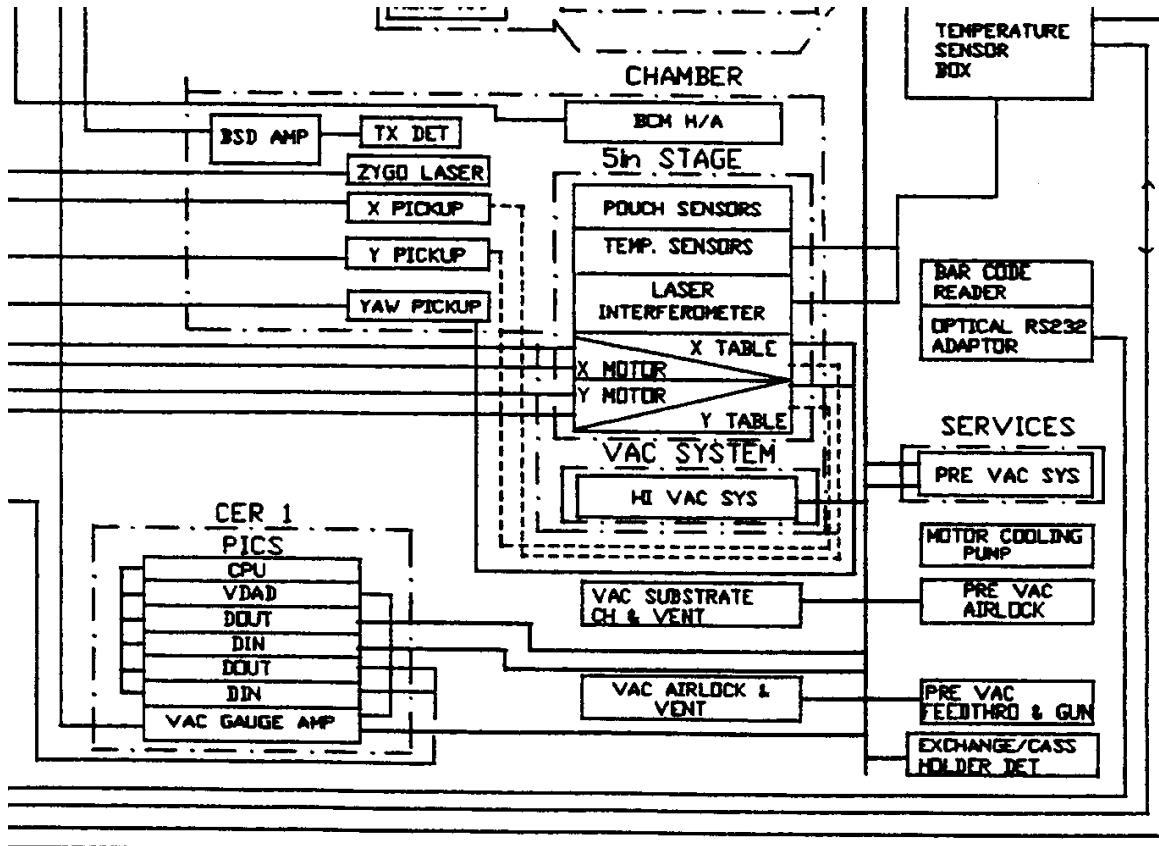
Deflection





System Architecture

Chamber

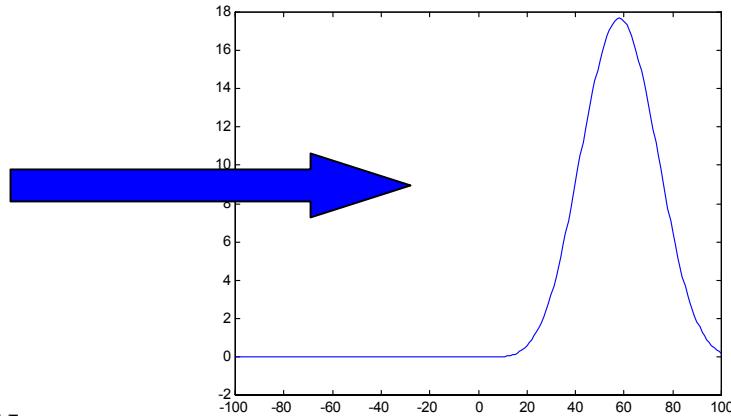




Correlation and convolution

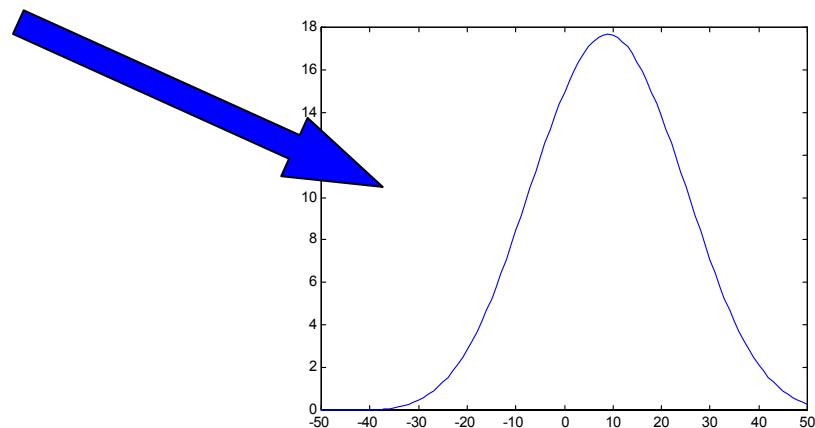
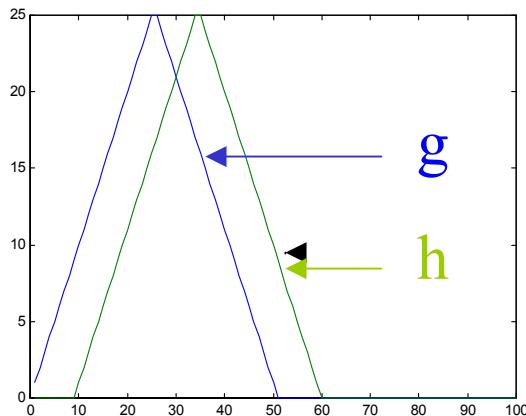
Convolution of \mathbf{h} and \mathbf{g} :

$$\mathbf{g} \otimes \mathbf{h} = \iint g(x-u, y-v) h(u, v) du dv$$



Correlation of \mathbf{h} and \mathbf{g} :

$$\langle \mathbf{g}, \mathbf{h} \rangle = \iint g(x+u, y+v) h(u, v) du dv$$





Correlation and convolution

Calculation of convolution using Fourier Transform

- Convolution Theorem
 - $p = h \otimes u$ the $P = (1/\pi)^2 H \bullet U$
 - Where “ \Leftrightarrow ” is the Fourier transform and
 - $p \Leftrightarrow P$, $h \Leftrightarrow H$, and $u \Leftrightarrow U$
- Fast Fourier Transform allows efficient calculation of “Periodic Convolution”





Correlation and convolution

Calculation of correlation using Fourier Transform

- Convolution Theorem
 - $p = \langle h, u \rangle$ the $P = (1/\pi)^2 H \bullet U^*$
 - Where “ \Leftrightarrow ” is the Fourier transform and
 - $p \Leftrightarrow P$, $h \Leftrightarrow H$, and $u \Leftrightarrow U$
- Fast Fourier Transform allows efficient calculation of “Periodic Correlation”





Correlation and convolution

- Correlation of a function with itself is called autocorrelation
- Autocorrelation is peaked at zero
- Relation between auto-correlation and the correlation of a shifted function with itself

$$A(x,y) = \langle g, g \rangle = \iint g(x+u, y+v)g(u, v)dudv$$

Shifted version

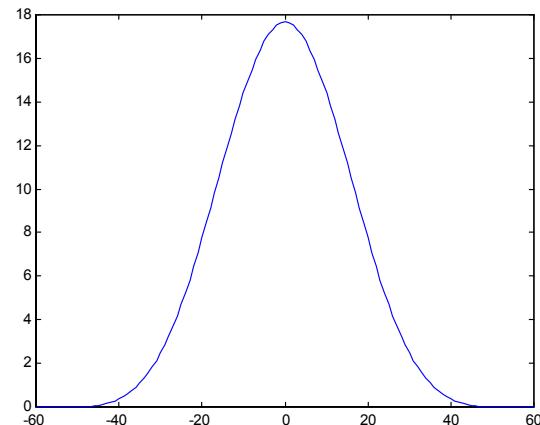
$$\langle g(x+ox, y+oy), g \rangle = \iint g(x+ox+u, y+oy+v)g(u, v)dudv$$

$= A(x+ox, y+oy)$ is just A shifted by ox and oy

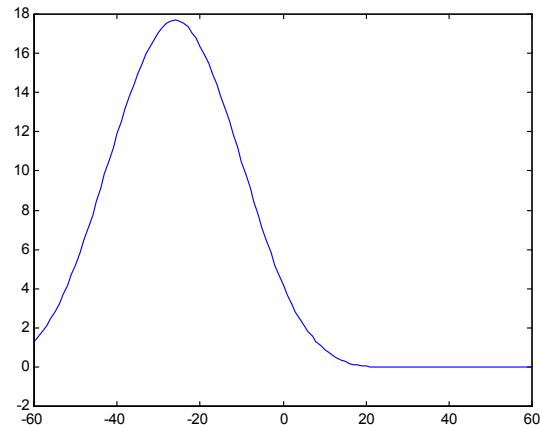




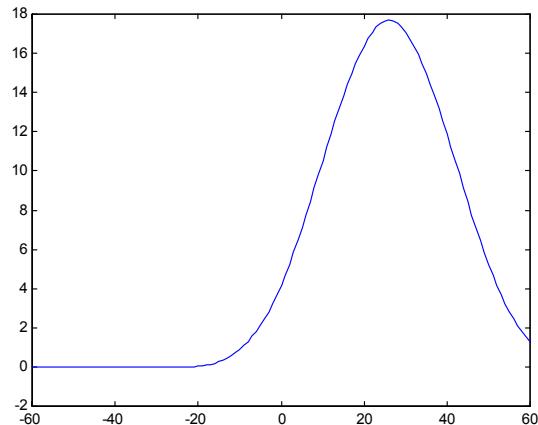
Correlation and convolution



$$\langle \mathbf{g}, \mathbf{g} \rangle$$



$$\langle \mathbf{g}(x+26), \mathbf{g} \rangle$$



$$\langle \mathbf{g}, \mathbf{g}(x+26) \rangle$$

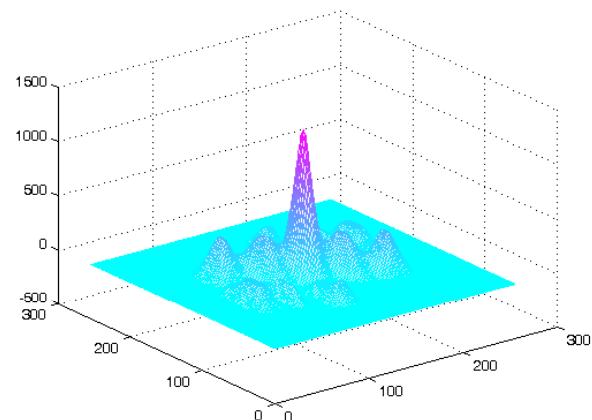
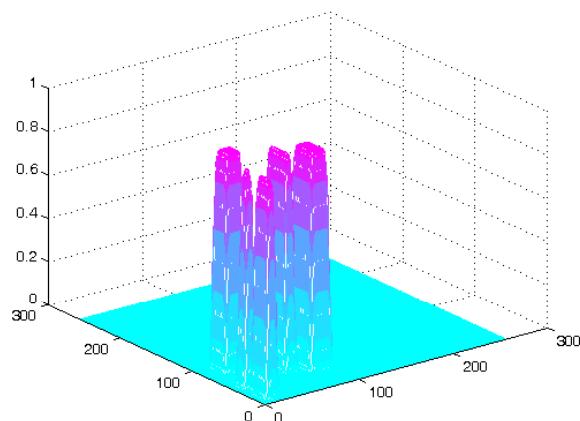
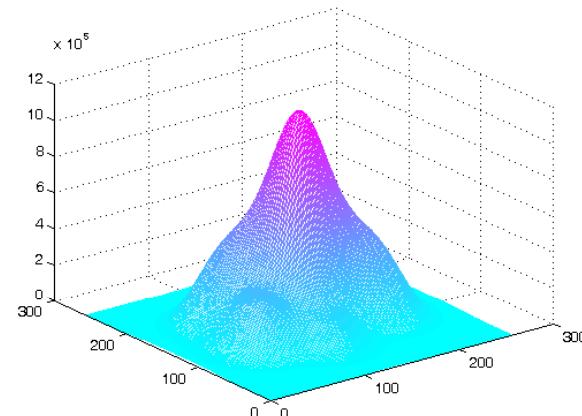
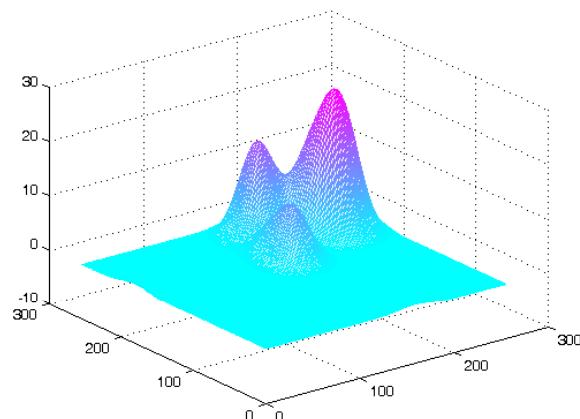


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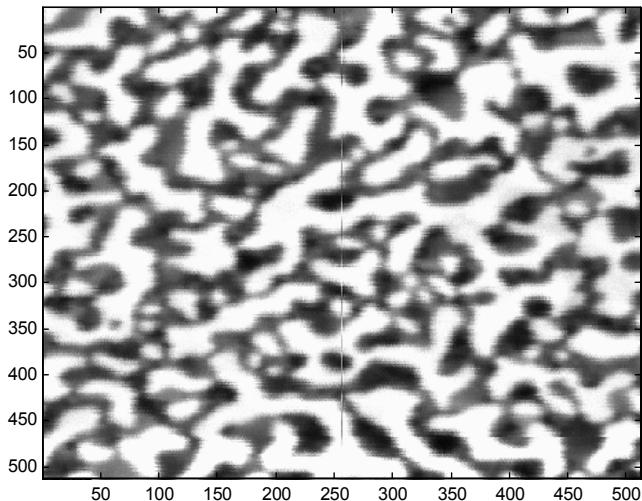


Correlation in two dimensions

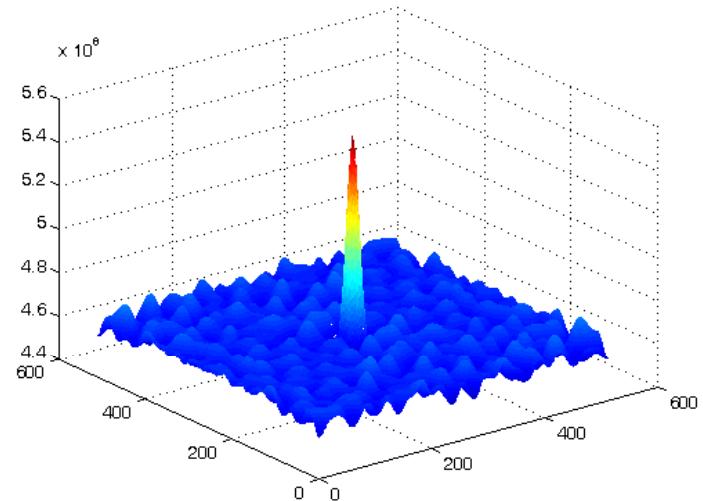




Correlation in two dimensions of Quasi-Random “Gold Islands”



Gold Island Image

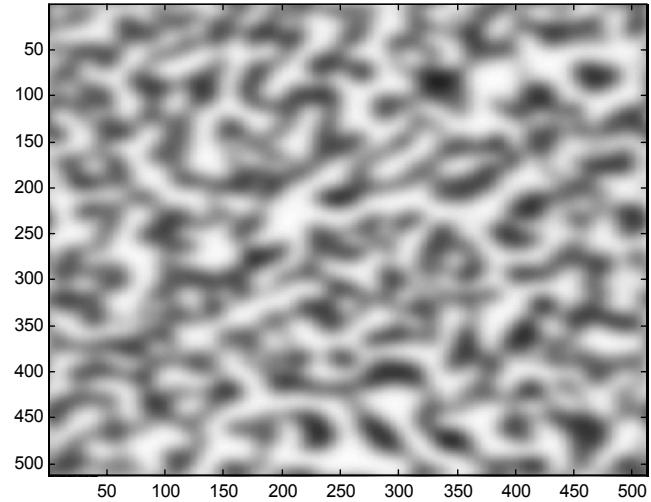
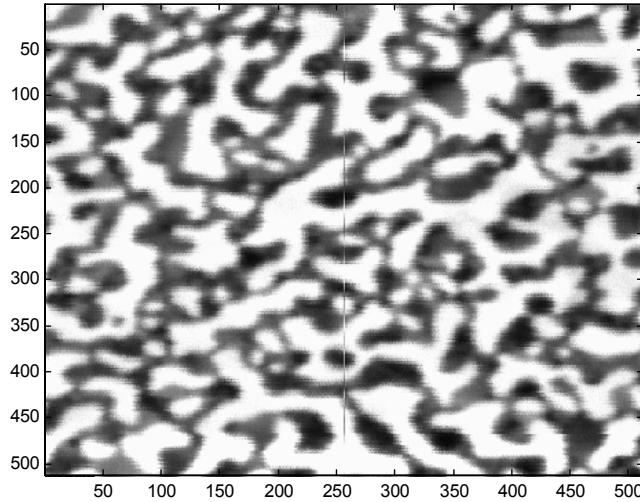


Gold Island
Autocorrelation

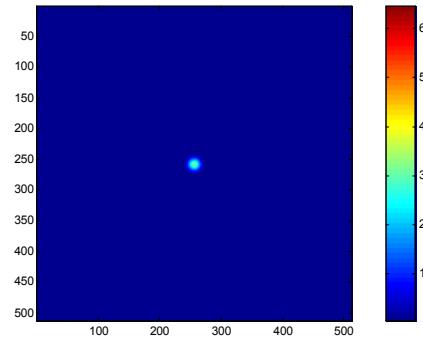




Focus/Stigmation using Autocorrelation

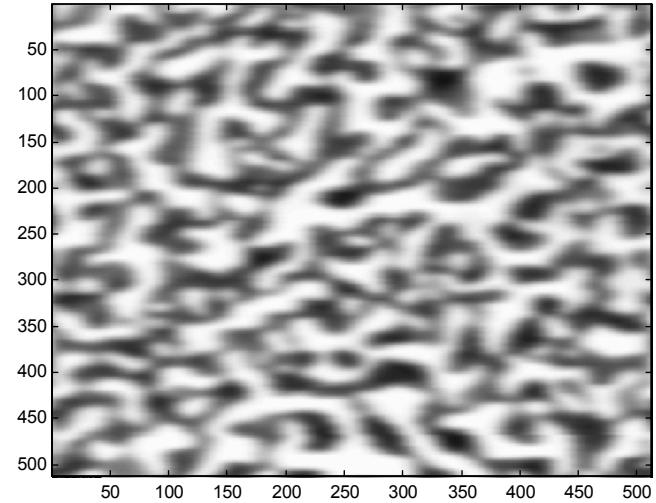
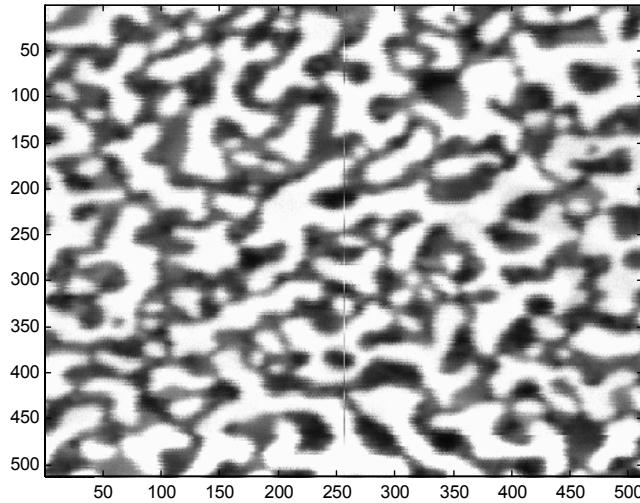


Defocus

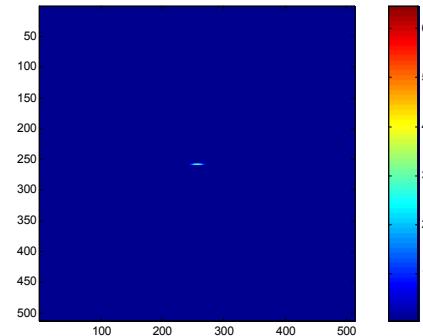




Focus/Stigmation using Autocorrelation

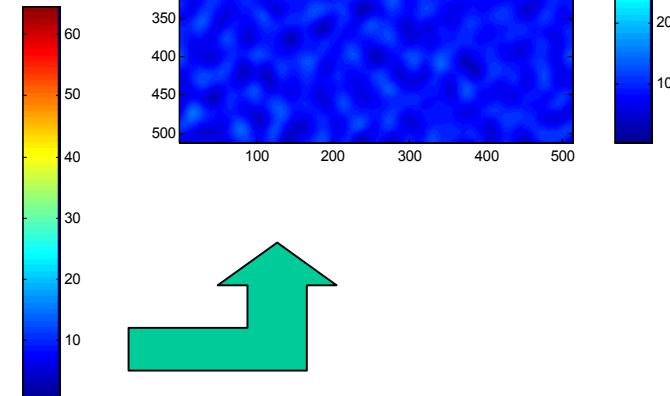
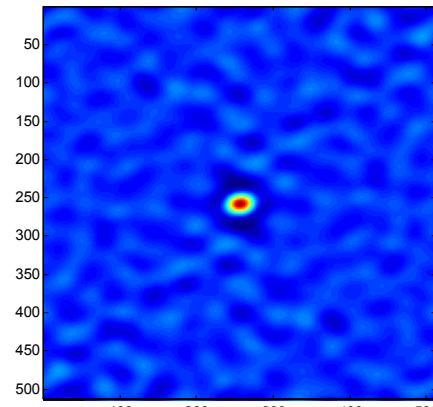
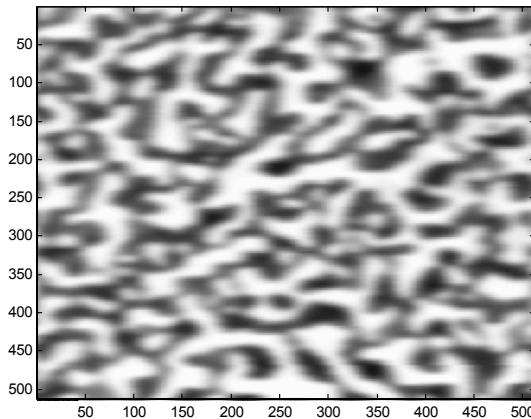
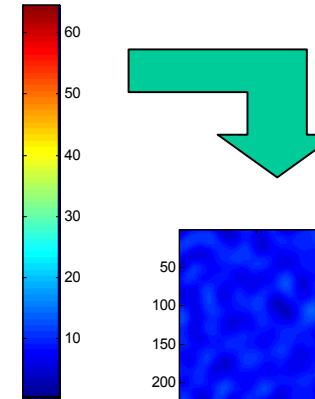
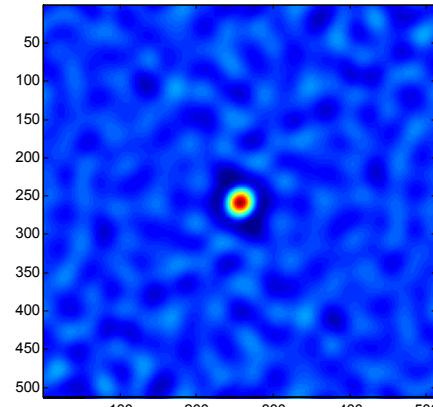
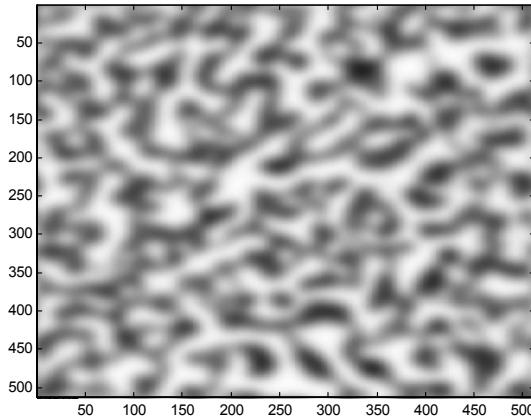


X Stigmation





Focus/Stigmation using Autocorrelation

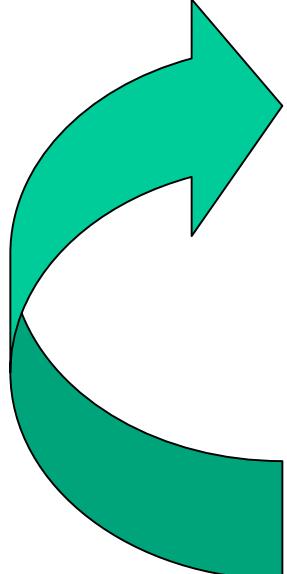


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Lecture 9 Alignment/Calibration



Focus/Stigmation using Autocorrelation

- 
- Image quasi-random pattern
 - Calculate autocorrelation function
 - slice and determine a second moment of radius of ellipse
 - minimize function adjusting Sx, Sy, and Focus
 - Repeat





Solving with more equations than unknowns: Singular Value Decomposition



Result from Linear Algebra:

- Any $M \times N$ matrix whose number of rows M is greater than or equal to its number of columns N can be written as the product of an $M \times N$ column-orthogonal matrix U , and $N \times N$ diagonal matrix W with positive or zero elements (the “singular values”) and the transpose of an $N \times N$ orthogonal matrix V





Singular Value Decomposition

$$A = U W V^T$$





$$\begin{array}{c} \text{Sqrt(eign)} \\ \left(\begin{array}{cccc} 107 & 95 & 43 & 83 \\ 95 & 89 & 55 & 88 \\ 43 & 55 & 107 & 107 \\ 83 & 88 & 107 & 125 \end{array} \right) = \left(\begin{array}{cccc} 1 & 3 & 9 & 8 \\ 5 & 4 & 5 & 6 \\ 9 & 8 & 1 & 5 \end{array} \right) * \left(\begin{array}{ccc} 1 & 5 & 9 \\ 3 & 4 & 8 \\ 9 & 5 & 1 \\ 8 & 6 & 5 \end{array} \right) \\ \left(\begin{array}{cccc} 107 & 95 & 43 & 83 \\ 95 & 89 & 55 & 88 \\ 43 & 55 & 107 & 107 \\ 83 & 88 & 107 & 125 \end{array} \right) = \left(\begin{array}{c} 0.9394 \\ 0 \\ 8.9951 \\ 18.6066 \end{array} \right) \end{array}$$





Ortho-normality of U and V

$$\mathbf{U}^T$$
$$\mathbf{U}$$
$$=$$
$$1$$


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Lecture 9 Alignment/Calibration



Ortho-normality of U and V

$$\begin{bmatrix} \mathbf{V}^T \end{bmatrix} \begin{bmatrix} \mathbf{V} \end{bmatrix} = \begin{bmatrix} 1 \end{bmatrix}$$





Inverse of a square matrix

$$\left[\begin{array}{c} \mathbf{A} \end{array} \right] = \left[\begin{array}{c} \mathbf{U} \end{array} \right] \left[\begin{array}{c} \mathbf{W} \end{array} \right] \left[\begin{array}{c} \mathbf{V}^T \end{array} \right]$$

$$\left[\begin{array}{c} \mathbf{A} \end{array} \right]^{-1} = \left[\begin{array}{c} \mathbf{V} \end{array} \right] \left[\begin{array}{c} \mathbf{W}^{-1} \end{array} \right] \left[\begin{array}{c} \mathbf{U}^T \end{array} \right]$$





More equations than unknowns

$$\left[\begin{array}{c} \mathbf{A} \\ \vdots \end{array} \right] \left[\begin{array}{c} \mathbf{x} \\ \vdots \end{array} \right] = \left[\begin{array}{c} \mathbf{b} \\ \vdots \end{array} \right]$$





More equations than unknowns

$$\left[\begin{array}{c} \mathbf{U} \\ \mathbf{W} \\ \mathbf{V}^T \end{array} \right] \left[\begin{array}{c} \mathbf{x} \end{array} \right] = \left[\begin{array}{c} \mathbf{b} \end{array} \right]$$





More equations than unknowns

$$\mathbf{x} = \mathbf{V} \left(\mathbf{W}^{-1} \mathbf{U}^T \right) \mathbf{b}$$





Examples: non-singular square matrix

$$\begin{bmatrix} 1 & 5 & 9 \\ 3 & 4 & 8 \\ 9 & 5 & 1 \end{bmatrix} = \begin{bmatrix} 0.6298 & 0.4577 & -0.6275 \\ 0.6066 & 0.2147 & 0.7654 \\ 0.4851 & -0.8628 & -0.1424 \end{bmatrix} \begin{matrix} \mathbf{U} \\ \mathbf{W} \\ \mathbf{V}^T \end{matrix}$$
$$\begin{bmatrix} 15.2189 & 0 & 0 \\ 0 & 8.3966 & 0 \\ 0 & 0 & 0.9391 \end{bmatrix}$$
$$\begin{bmatrix} 0.4478 & 0.5257 & 0.7232 \\ -0.7936 & -0.1389 & 0.5924 \\ 0.4119 & -0.8392 & 0.3550 \end{bmatrix}$$





Examples: non-singular square matrix

$$\begin{bmatrix} 0.6298 & 0.4577 & -0.6275 \\ 0.6066 & 0.2147 & 0.7654 \\ 0.4851 & -0.8628 & -0.1424 \end{bmatrix} \begin{bmatrix} 0.6298 & 0.6066 & 0.4851 \\ 0.4577 & 0.2147 & -0.8628 \\ -0.6275 & 0.7654 & -0.1424 \end{bmatrix}^T = \begin{bmatrix} 1.0000 & 0.0000 & 0.0000 \\ 0.0000 & 1.0000 & 0.0000 \\ 0.0000 & 0.0000 & 1.0000 \end{bmatrix}$$

$$\begin{bmatrix} 0.4478 & -0.7936 & 0.4119 \\ 0.5257 & -0.1389 & -0.8392 \\ 0.7232 & 0.5924 & 0.3550 \end{bmatrix} \begin{bmatrix} 0.4478 & 0.5257 & 0.7232 \\ -0.7936 & -0.1389 & 0.5924 \\ 0.4119 & -0.8392 & 0.3550 \end{bmatrix}^T = \begin{bmatrix} 1.0000 & 0.0000 & 0.0000 \\ 0.0000 & 1.0000 & 0.0000 \\ 0.0000 & 0.0000 & 1.0000 \end{bmatrix}$$





Examples: singular square matrix

$$\begin{bmatrix} 1 & 5 & 9 \\ 3 & 4 & 8 \\ 2 & 10 & 18 \end{bmatrix} = \begin{bmatrix} 0.4152 & 0.1661 & 0.8944 \\ 0.3714 & -0.9285 & 0.0000 \\ 0.8304 & 0.3322 & -0.4472 \end{bmatrix} \begin{bmatrix} 24.8995 & 0 & 0 \\ 0 & 2.0041 & 0 \\ 0 & 0 & 0.0000 \end{bmatrix} \mathbf{W}$$

Singular value!

$$\mathbf{V}^T = \begin{bmatrix} 0.1281 & 0.4766 & 0.8698 \\ -0.9754 & 0.2191 & 0.0237 \\ 0.1792 & 0.8514 & -0.4929 \end{bmatrix}$$





Examples: non-square matirx

$$\begin{pmatrix} 1 & 3 & 2 \\ 4 & 9 & 6 \\ 1 & 7 & 9 \\ 9 & 9 & 2 \\ 8 & 8 & 4 \end{pmatrix} = \begin{pmatrix} 0.1587 & 0.1029 & -0.3233 \\ 0.4981 & 0.2247 & -0.6008 \\ 0.4264 & 0.7396 & 0.3225 \\ 0.5294 & -0.5532 & -0.2036 \\ 0.5144 & -0.2932 & 0.6237 \end{pmatrix} \begin{pmatrix} 22.7943 & 0 & 0 \\ 0 & 8.1473 & 0 \\ 0 & 0 & 1.4280 \end{pmatrix} \begin{pmatrix} 0.5026 & 0.7381 & 0.4501 \\ -0.6852 & 0.0226 & 0.7280 \\ 0.5271 & -0.6743 & 0.5171 \end{pmatrix} \mathbf{V}^T$$





Meaning of solution vector

What does the solution for more equations than variables mean?

- If $r = \| \mathbf{Ax} - \mathbf{b} \|$ is the residual then r is minimized with the SVD solution of $\mathbf{x} = \mathbf{V} \mathbf{W}^{-1} \mathbf{U}^T \mathbf{b}$





Singular or almost singular situations

When the diagonal value, d_i is zero, or almost zero the set of equations is singular or almost singular. The procedure is to replace $1/d_i$ zero if d_i is too small. A test is made relative to the largest singular value d_0 and the expected precision.

- if $d_i < \epsilon d_0$ then $1/d_i = 0$





Distortion correction with Polynomials and SVD



$$Px = a_0 + a_1x + a_2y + a_3xy + a_4x^2 + a_5y^2 + a_6xy^2 + a_7x^2y + a_8x^2y^2$$

$$Py = b_0 + b_1x + b_2y + b_3xy + b_4x^2 + b_5y^2 + b_6xy^2 + b_7x^2y + b_8x^2y^2$$

- 18 unknowns require 18 or more equations

$$\begin{matrix} 1 & x & y & xy & x^2 & y^2 & xy^2 & x^2y & x^2y^2 \\ 1 & x & y & xy & x^2 & y^2 & xy^2 & x^2y & x^2y^2 \\ 1 & x & y & xy & x^2 & y^2 & xy^2 & x^2y & x^2y^2 \\ 1 & x & y & xy & x^2 & y^2 & xy^2 & x^2y & x^2y^2 \\ 1 & x & y & xy & x^2 & y^2 & xy^2 & x^2y & x^2y^2 \end{matrix} \quad \left. \right\} \quad \begin{matrix} a \\ = \\ Px \end{matrix}$$





Focus and Stigmatation

Model focus and stigmatation with second order:

$$F = a_0 + a_1x + a_2y + a_3xy + a_4x^2 + a_5y^2$$

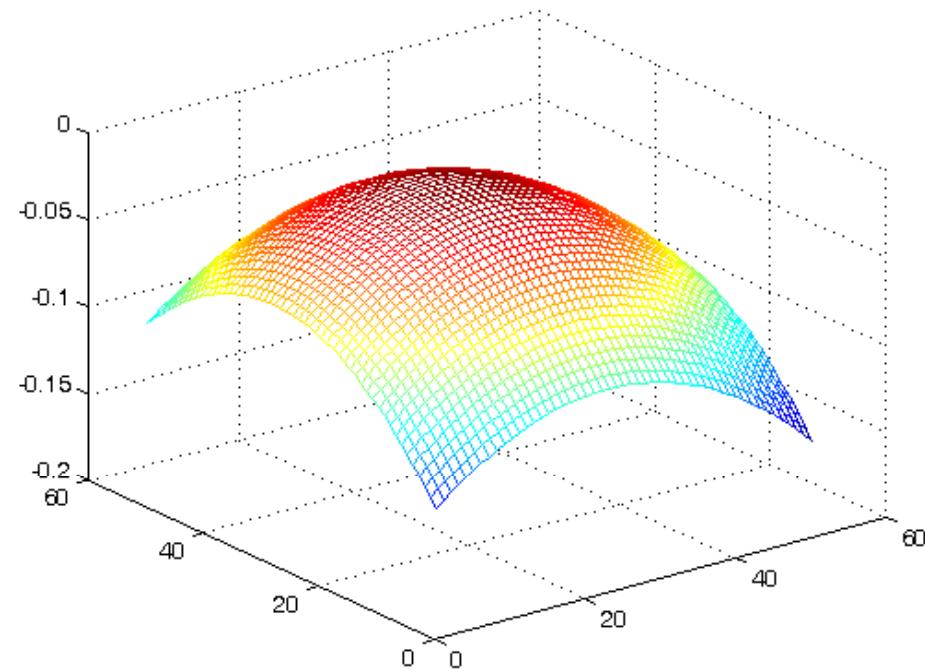
$$F = b_0 + b_1x + b_2y + b_3xy + b_4x^2 + b_5y^2$$

$$F = c_0 + c_1x + c_2y + c_3xy + c_4x^2 + c_5y^2$$





Focus and Stigmatation Data

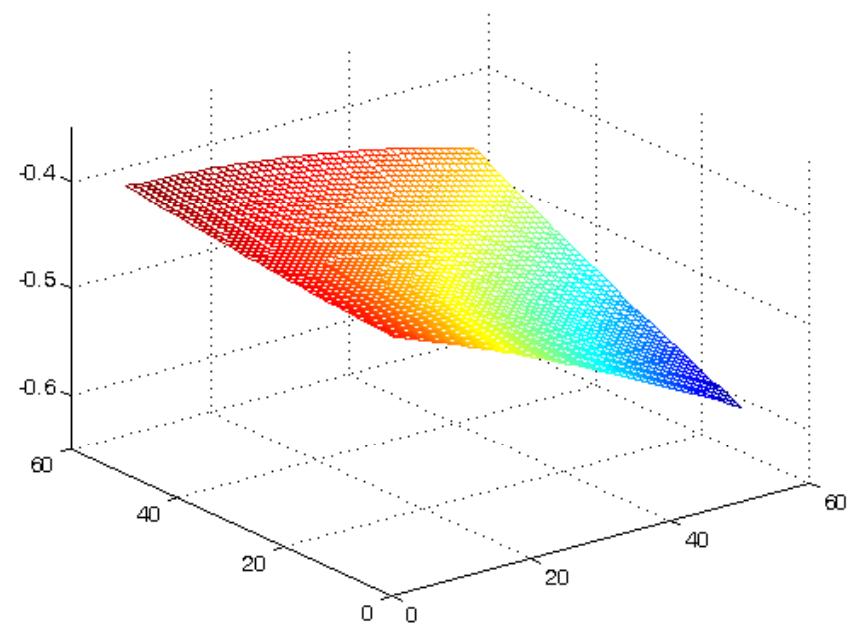
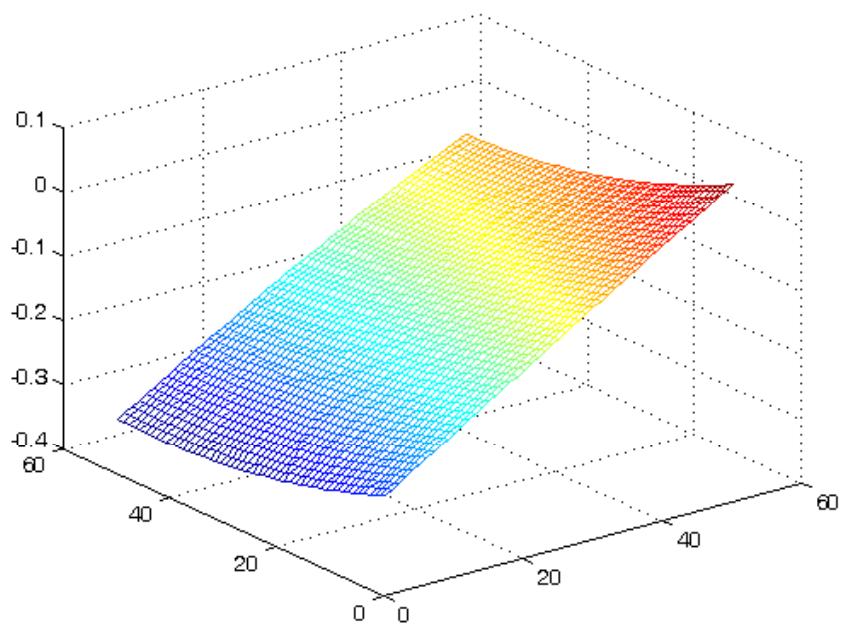


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Focus and Stigmation Data

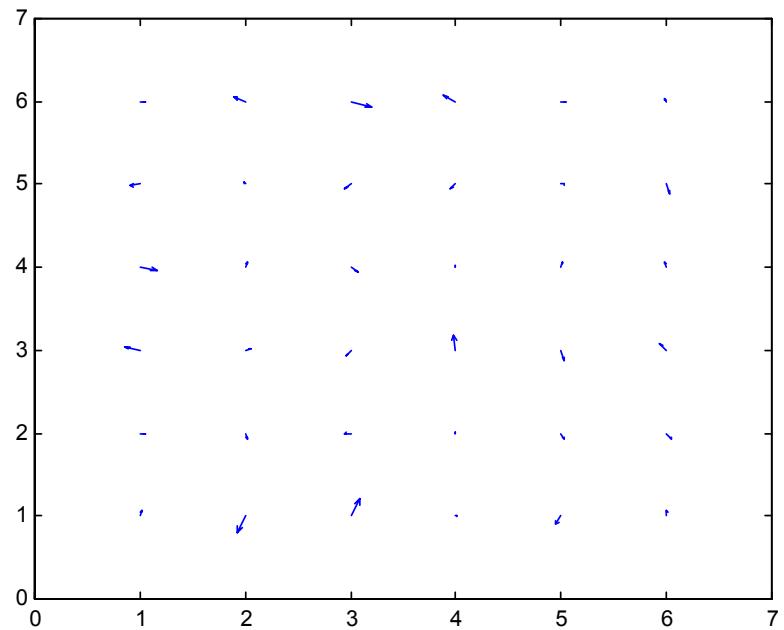
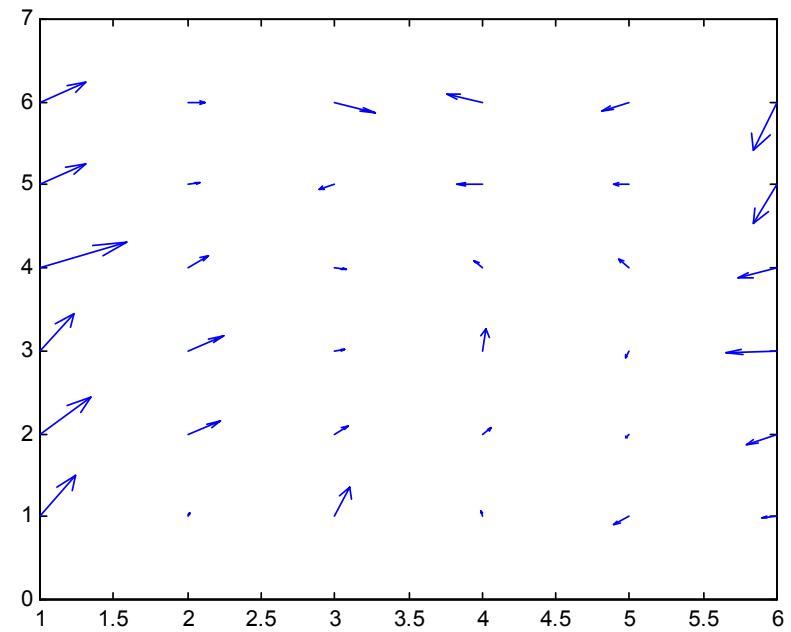


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Lecture 9 Alignment/Calibration



Distortion Data

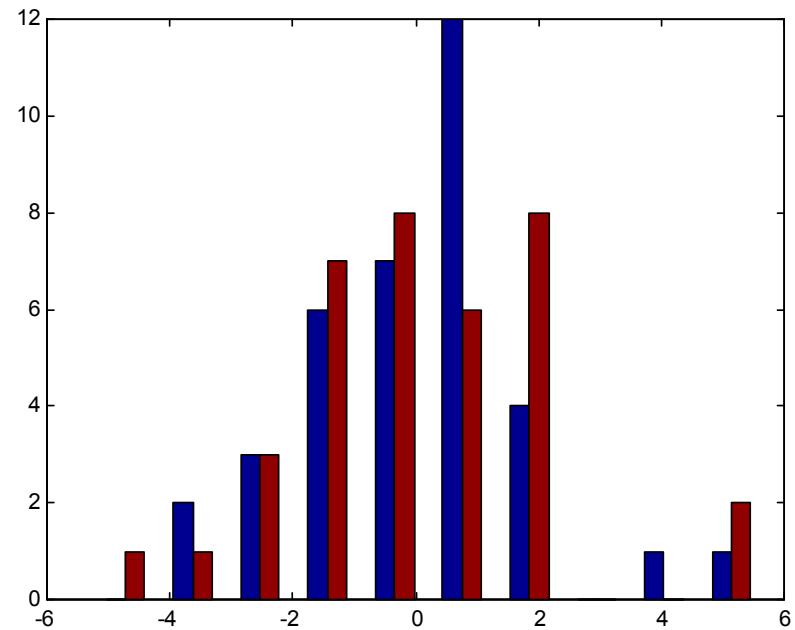
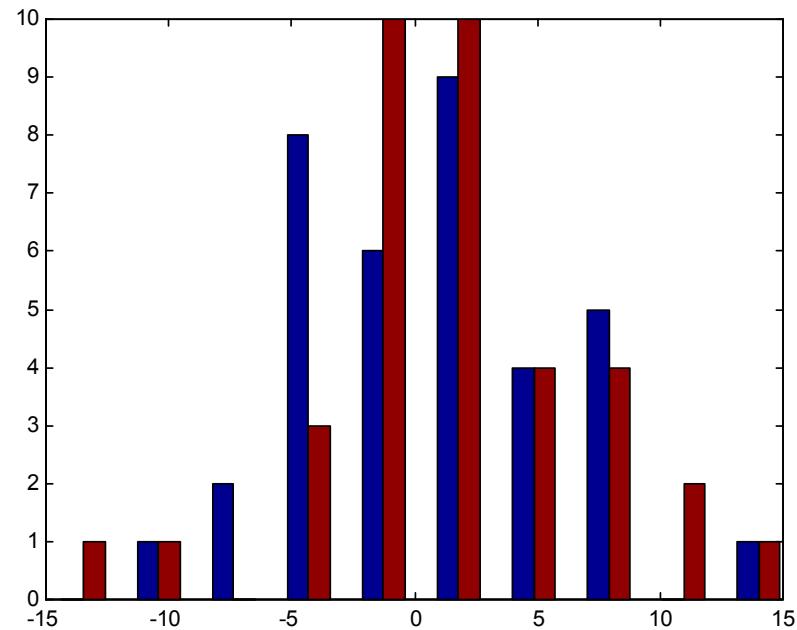


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Lecture 9 Alignment/Calibration



Distortion Data after non-linear fit





Mark Location

Critical element to calibration because almost all accuracy depends on mark alignment in one way or another

- Use cross-correlation to find approximate offset
- Fit center part of autocorrelation function to cross-correlation using SVD.
- Move fitted function around and minimize least square value to get sub-pixel accuracy





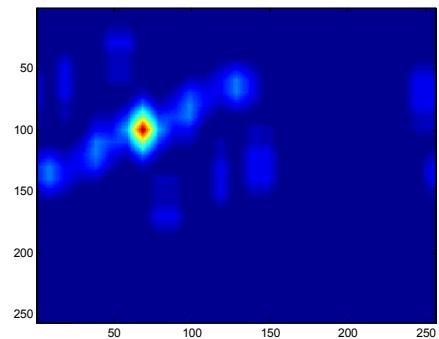
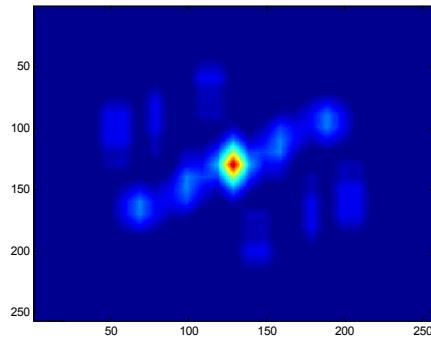
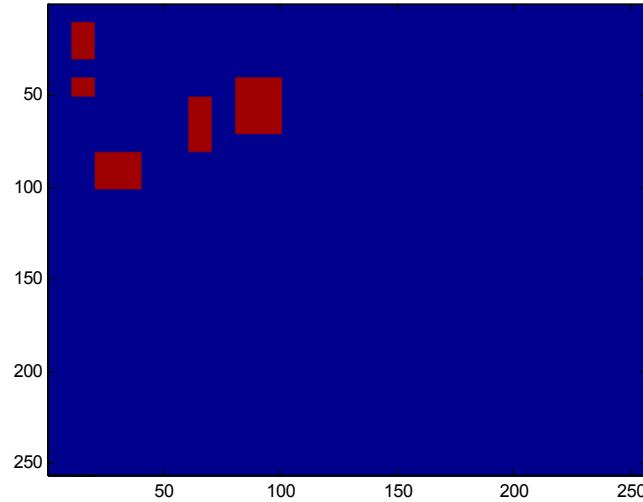
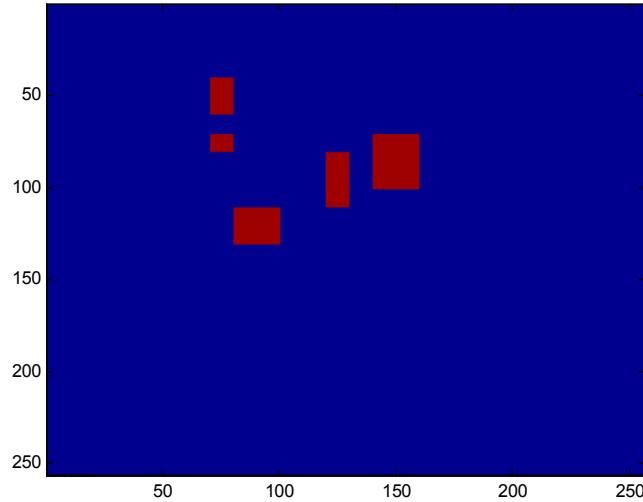
Mark Location

```
% this function takes an image and a template  
% and returns dx and dy offsets of the correlation  
% to cross correlation by minimizing the least square  
% fit of the shifted cross to auto correlation of the image;  
function [del, gain] = marklk2(ccf,acf,c,ns);  
% del is the offset  
% gain is the magnitude of the image  
% acf is the autocorelation function (should be even in size)  
% ccf is the cross correlation function (should be same size as acf)  
% c is the search range typically 3 i.e. +3 to -3  
% ns is the reduced size of the auto and cross correlation functions  
% the array is nsXns.
```





Mark Location



$$\text{Offset} = [30, 60]$$

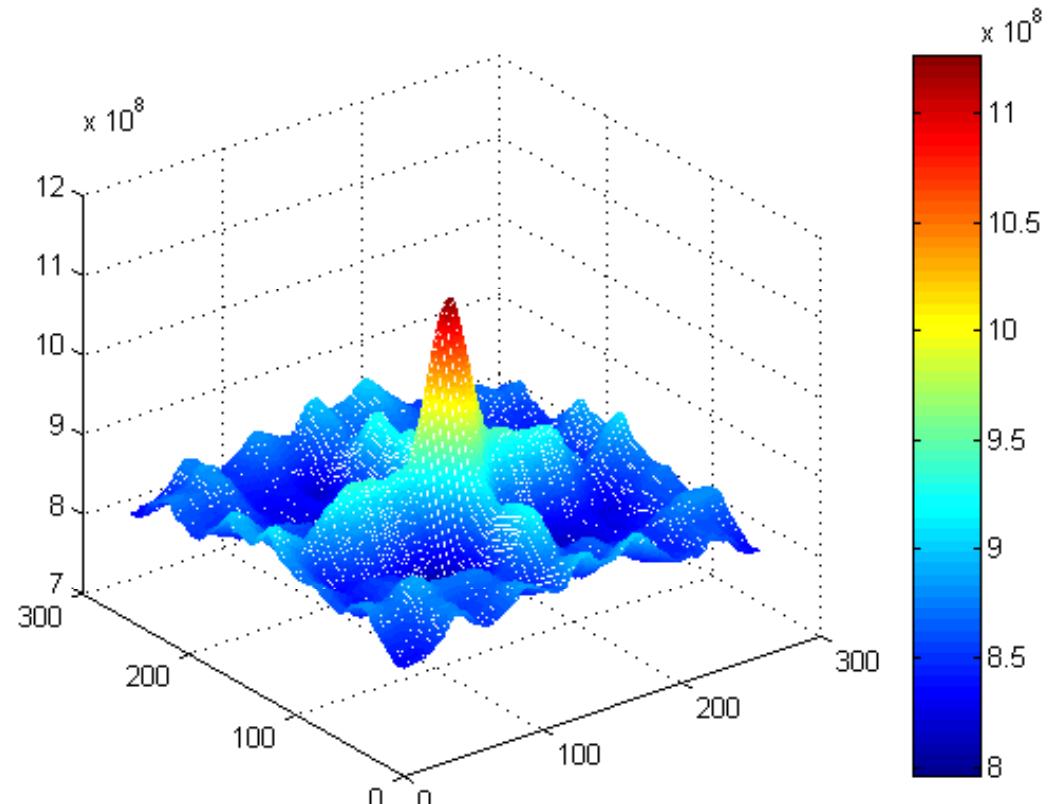
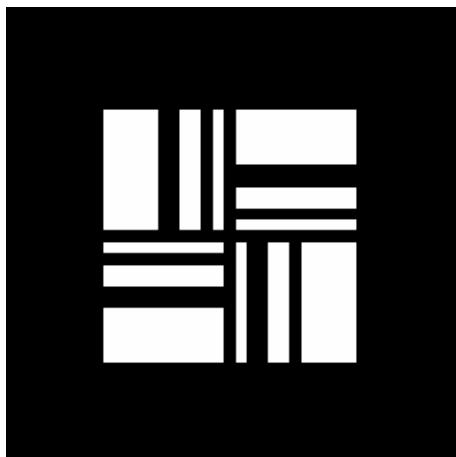
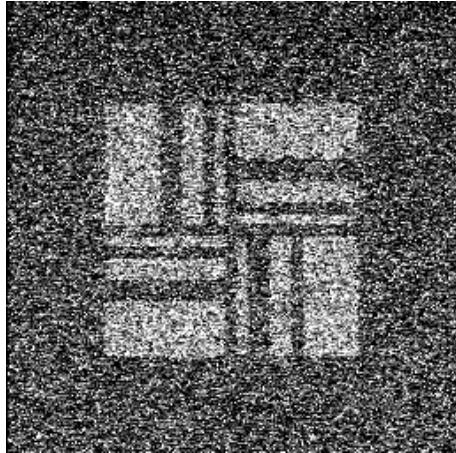


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Lecture 9 Alignment/Calibration



Image & Template Cross-correlation



$$\text{Corr}(A, B)[x, y] = \sum_{j=1}^N \sum_{i=1}^N A(j, i)B(j + x, i + y)$$



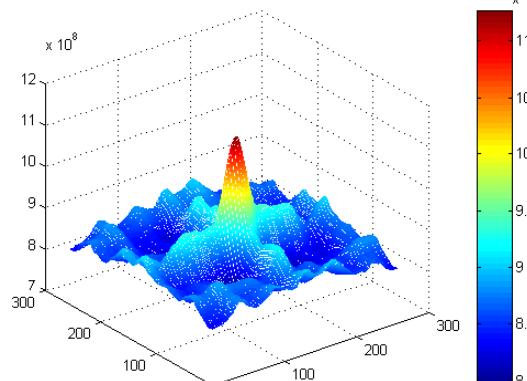
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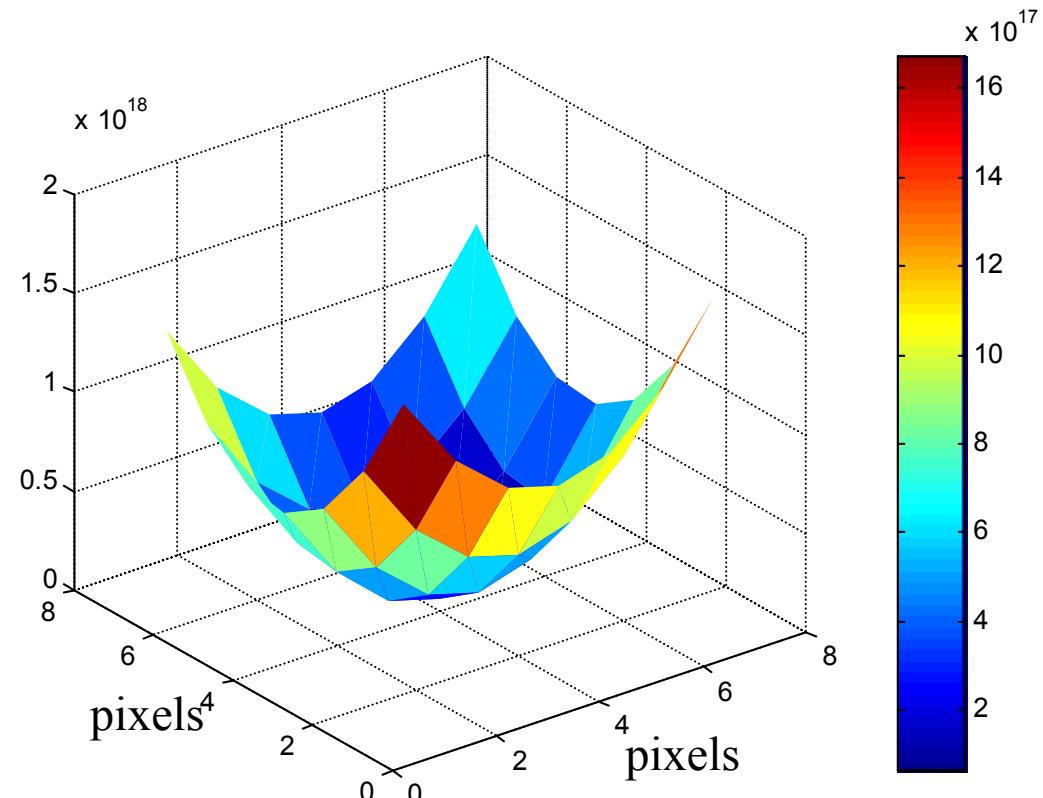


Residual Value Calculation for sub Pixel accuracy

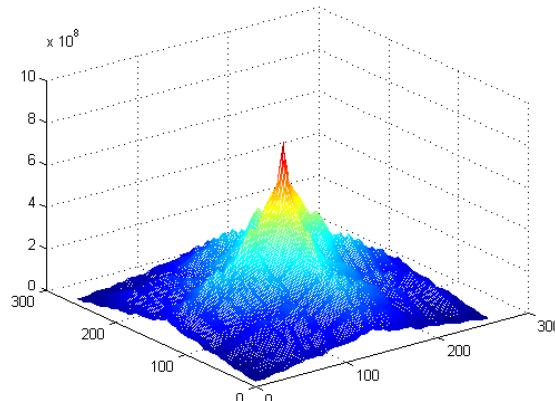
Cross-correlation function



Residual values around cross-correlation peak



Auto-correlation function

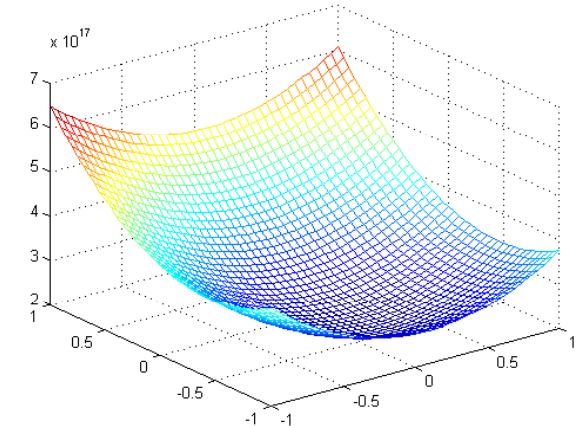
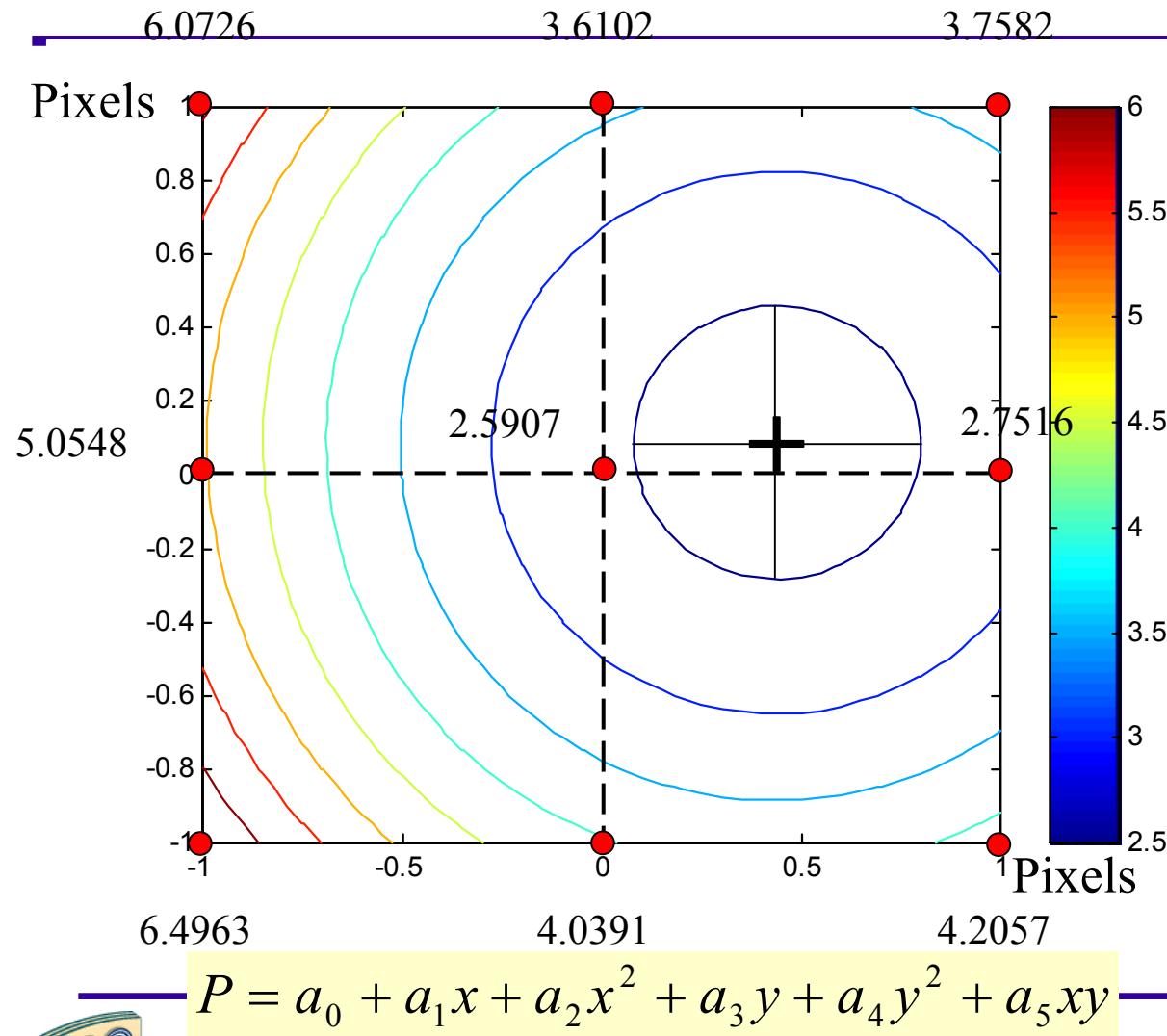


$$\text{ACF fit to CCF: } \text{CCF} = a_0 + a_1 \text{ACF}$$





Sub-Pixel calculation using SVD fit to residuals

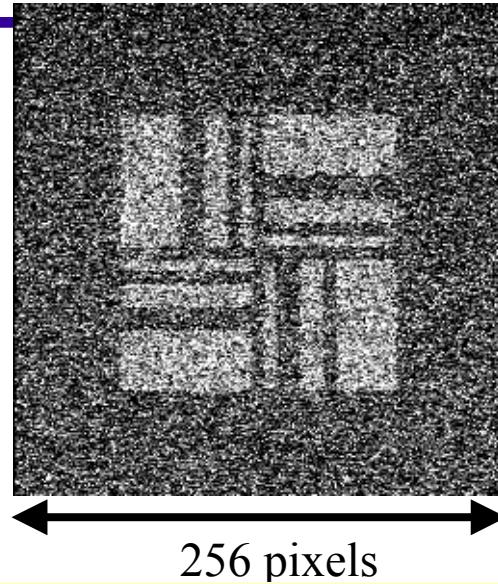
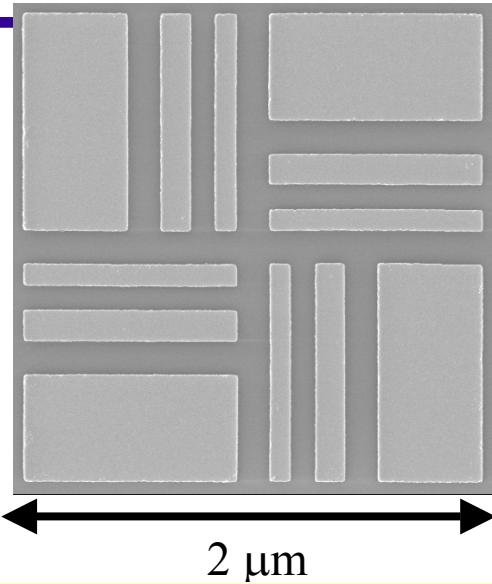


Mark locations are determined to sub-pixel accuracy by calculating analytically polynomial minimum.





Barker Code Alignment Marks



50 nm Au/5 nm Cr

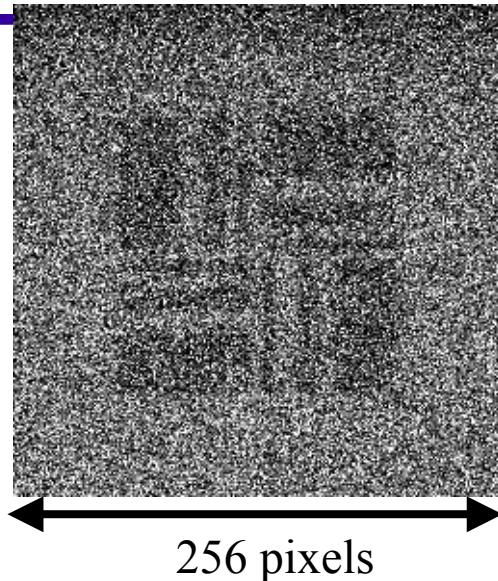
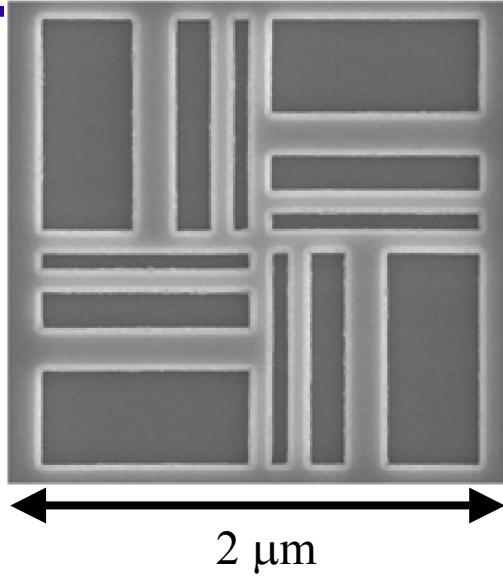
Alignment accuracy is linear in pixel size

Mark	Pixel (nm)	$3\sigma_x$	$3\sigma_y$	3σ
Barker 1	5	1.9	2.0	2.8
Cross	5	2.4	2.6	3.5
Barker 1	10	3.0	3.1	4.3
Barker 2	20	6.4	5.3	8.3
Barker 2	40	8.8	8.7	12.4





Low contrast alignment marks



360 nm etch depth in Si

Alignment accuracy is linear in pixel size

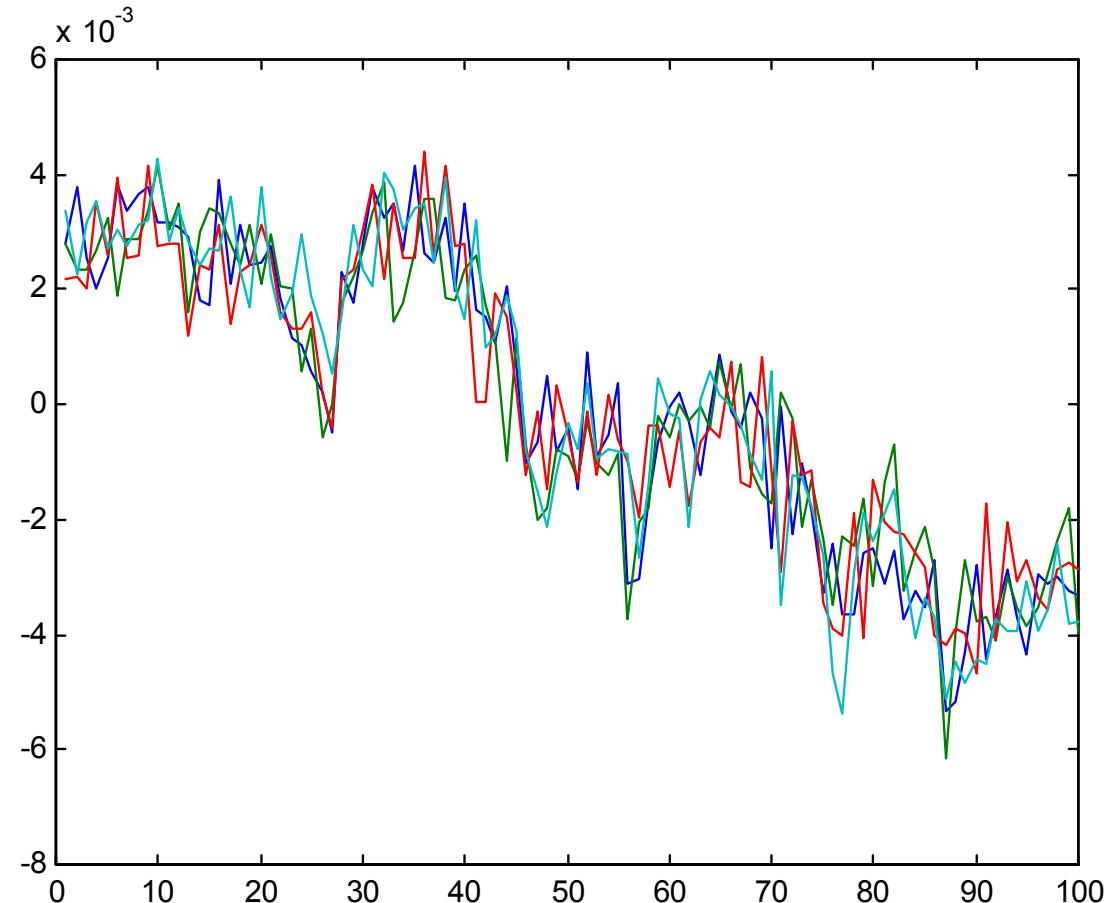
Pixel (nm)	3 σ (nm) No resist	3 σ (nm) Resist
10	14.8	19.7
20	18.3	30.1
40	25.7	33.4
80	47.7	48.0





Drift Data with good Alignment Marks

Position

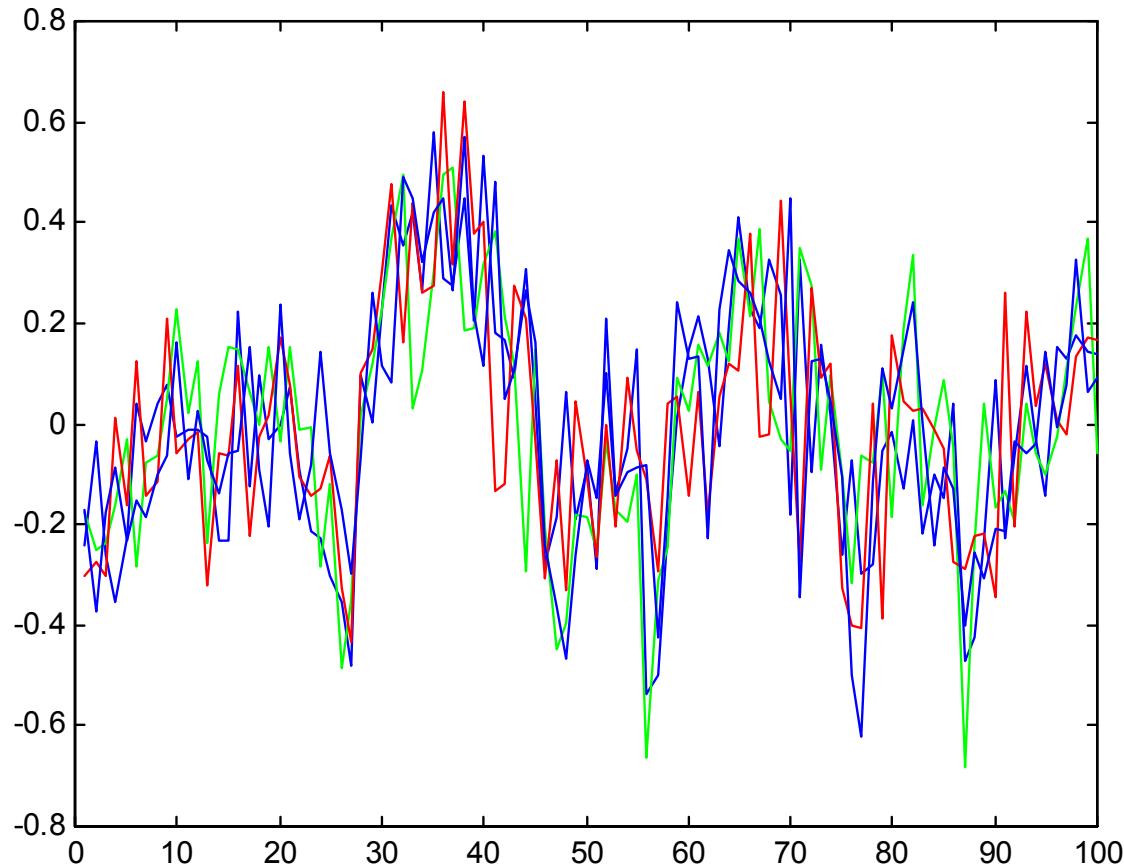


E298A/EE290B

Measurement Number (time)
Lecture 9 Alignment/Calibration

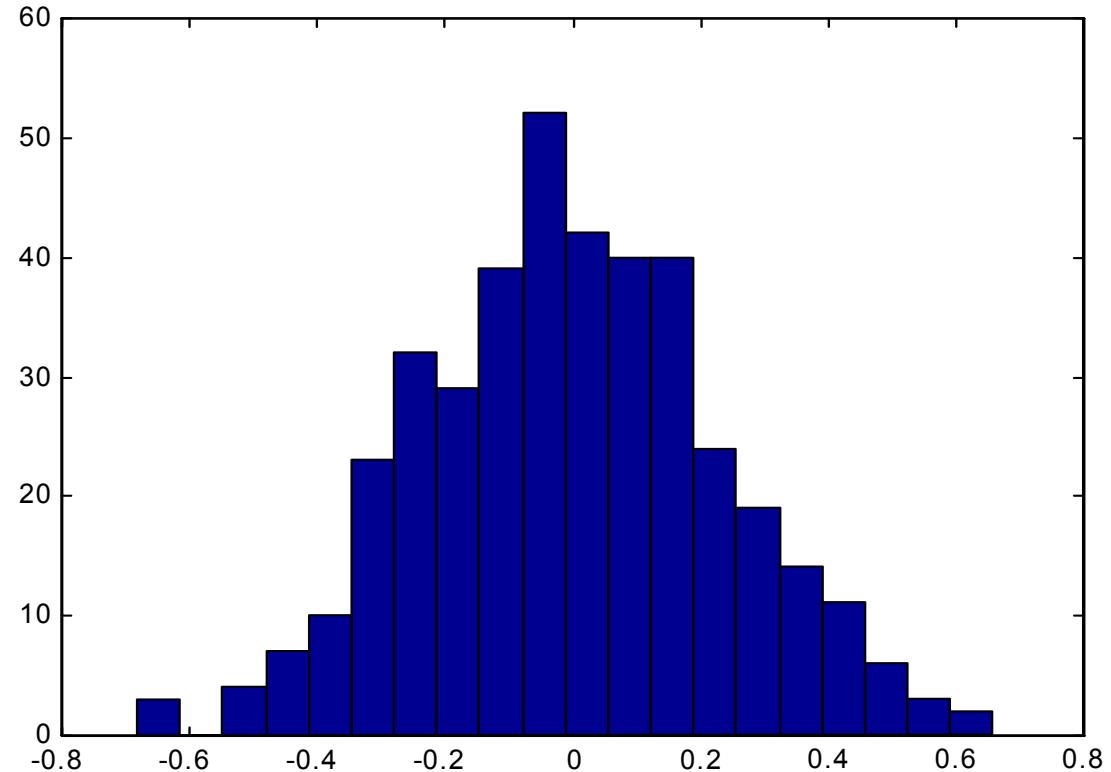


Take out linear drift from raw data



- Realign during exposure (assumed linear drift)





$3\sigma = 3.5\text{nm}$

Pixel = 5nm

Histogram of data with linear drift removed





Calibration sequence

- Laser feedback
- Distortion
- Major to Minor
- (height)
- Major to rotated coordinates
- Minor to Major

